IDA

INSTITUTE FOR DEFENSE ANALYSES

Modeling the User for Education, Training, and Performance Aiding

Robert E. Foster
J. D. Fletcher

November 2003
Approved for public release;
distribution unlimited.
IDA Document D-2920
Log: H 03-002415

This work was conducted under contracts DASW01 98 C 0067/ DASW01 04 C 0003, Task AK-2-2349, for ODUSD(S&T) (Human Systems). The publication of this IDA document does not indicate endorsement by the Department of Defense, nor should the contents be construed as reflecting the official position of that Agency.

INSTITUTE FOR DEFENSE ANALYSES

IDA Document D-2920

Modeling the User for Education, Training, and Performance Aiding

Robert E. Foster
J. D. Fletcher

PREFACE

This study was conducted for the Director, Defense Research and Engineering (DDR&E) under the "Science and Technology Support for Training Transformation and the Human Systems Technology Area" task. Technical cognizance for this task is assigned to Dr. Robert Foster, Director, BioSystems.

The authors express their thanks to the North Atlantic Treaty Organization (NATO) Human Factors and Medical Panel for their review of this document and its inclusion in their Fall 2003 symposium on *Advanced Technologies for Military Training*.

CONTENTS

TABLES

EXECUTIVE SUMMARY

If we are to present instruction that is available anytime and anywhere, takes advantage of the substantial tutorial efficiencies of one teacher for every student, and is affordable, we must have recourse to technology—specifically, computer technology. Such technology can be used in instructional applications that range from drill and practice and tutorial dialogues, to multiplayer simulations and games. It can be used in stand-alone modes, or it can be used to supplement classroom instruction. It can be used by individuals or by groups. In all cases, however, it must take account of the current state of the learner, the eventual state of the learner that the instruction is intended to produce, and the instructional techniques that reliably effect transitions from one state to the other.

Models of the learner that represent these current and objective states must, to an appreciable extent, be models of the learner's cognition, something that underlies competence and produces the human skills, performance, and abilities needed for success in all military operations. These models can be implicit, as in intrinsically programmed instruction, or they can be explicit. Both types have been used in technology-based instruction from its beginning.

Early explicit models were largely quantitative. These models involved relatively simple instructional paradigms but fairly elaborate mathematics, including instructional applications of optimal control theory. Current efforts are more concerned with qualitative models, 19 of which are briefly described and discussed. Each of these models can contribute to the efficiency and effectiveness of technology-based instruction. However, new challenges have arisen from today's uncertain, asymmetric operational environment, and these challenges may require responses that cannot be foreseen or be well prepared for in advance.

Our military personnel must be prepared to expect the unexpected and to meet unexpected events with individual and collective agility, creativity, and adaptability. These qualities are fundamentally cognitive in nature and require more powerful and comprehensive cognitive models if they are to serve our programs of education, training, decision-making, and performance aiding successfully.

MODELING THE USER FOR EDUCATION, TRAINING, AND PERFORMANCE AIDING

A. INTRODUCTION

This document addresses research on digital representations of human cognitive processes that can be used to develop computer-mediated learning and performance-aiding systems. We refer to such representations as "models" of human cognition. Since this topic is extensive in breadth and depth, we focused our discussion on the following questions:

- What is the military value of these models?
- What is their current state of development?
- What is their relationship to instructional systems development?
- What research and development (R&D) should be undertaken to advance their value and utility?

Many valuable contributions are being made by researchers who are modeling neurological activity at one end of the behavioral spectrum and by researchers who are modeling human physical activity and performance at the other end. This document is aimed somewhere in the middle of these efforts. It concerns models, or representations, of human cognitive processes such as perception, memory, learning, decision-making, and problem solving. These processes arise from "micro" neurological activity at one end of the spectrum and, in turn, produce "macro" physical activity and performance at the other end. Eventually, R&D may yield models that unify the full spectrum of human behavior, from neurons to psychomotor activity; however, the current state of knowledge limits us to efforts to understand and model components of this spectrum. Hence, this document focuses on one such component, cognition, which seems an appropriate level of concern for learning and human performance.

The term "the user" is used throughout this document. This term is intended as a catch-all for students, decision-makers, technicians, analysts, and anyone else who may be using computer technology for education, training, decision-making, and performance aiding. Our focus is on the digital representation of these users' cognitive processes.

B. THE MILITARY VALUE OF COGNITIVE MODELING

An obvious and frequently neglected fact is that human competence, which is a product of human cognition, is essential to every military operation across all echelons of command and activity. Its importance is perennially evident in the conduct of military operations. Even in the increasingly technology-saturated environments of modern operations, human competence is needed to launch and control systems in space, to operate and maintain robotic vehicles, to deploy remote sensors and systems in contested territory, and so forth. In short, we have no unmanned systems. Without competent people to operate, maintain, and deploy our materiel assets, investments in these assets will return little and may, in fact, be wasted. Given the wide availability of technology and the ease with which it can be obtained, human competence may increasingly account for the difference between success and failure in military operations. Its availability to commanders anytime and anywhere is a matter of first importance.

How can we ensure this availability? Training (and its performance-aiding analog) provides one means to accomplish this objective, particularly if this training can be delivered anytime and anywhere. For example, we might supply each user with an omnipresent tutor. Such tutoring is probably best done by a human who possesses expertise in the relevant subject matter, by a comprehensive range of tutorial techniques, and by sufficient knowledge of the user to identify, establish, and sustain in that individual the precise human competence needed. Research has shown such tutoring to be extremely effective, producing an often-noted two standard deviations of improvement over less accessible and less effective classroom instruction (Bloom, 1984). However, such an approach has also been called an instructional imperative and an economic impossibility because, for obvious reasons, a human tutor cannot be supplied to every user. This situation creates a gap between what is needed and what we can afford. As in many other endeavors, technology is being applied to fill this gap.

The research evidence suggests that such applications of technology can succeed. In nearly 300 studies comparing classroom (one teacher, many students) with computer-mediated, individualized instruction (one computer, one student) across many different settings and subject matters, a "rule of thirds" emerges. That is, compared with classroom instruction, technology-based instruction costs about a third less and also either increases achievement by a third when instructional time is held constant or decreases time to reach constant levels of achievement by about a third. Fletcher (1997, 2002), Foster and Fletcher (2002), Kulik (1994), Niemiec, Sikorski, and Walberg (1989), and others have presented more

detailed discussions of these data. The primary payoff for military operations is the more rapid and reliable preparation of personnel to perform operational duties, which produces significant payoffs for resource expenditures, readiness, and, most importantly, operational effectiveness.

Similar research evidence exists in support of technology used to aid performance and decision-making. For instance, technicians with only general training have been found to perform as well as specialists (who required time-consuming and expensive training) if they are provided hand-held or wearable performance aids (e.g., Fletcher and Johnston, 2002; Joyce, 2001; Wisher and Kinkaid, 1989). These aids contribute to military readiness and effectiveness not only by enabling individuals to be released earlier for operational duty, but also by improving human competence for maintaining, operating, and deploying materiel assets—thereby significantly improving materiel readiness.

Costs are also a factor. For instance, the United States military spends about $4 billion a year on specialized skill training. This is the training provided after "basic" or accession training to qualify personnel for the many technical jobs (e.g., wheeled vehicle mechanics, radar operators, avionics technicians, oceanographers, medical technicians) needed to perform military operations. It does not include aircraft pilot training, field training, or factory training, which are covered in separate cost categories. If the United States were to reduce by 30 percent the time to train 20 percent of the personnel undergoing specialized skill training, it would save over $250 million per year. If it were to do so for 60 percent of the personnel undergoing specialized skill training, it would save over $700 million per year (Foster and Fletcher, 2002). These are appreciable savings by most standards.

What do these analyses and observations have to do with cognitive modeling? Effective education and training must start with a dynamic and updateable understanding, or model, of the current state of the user—a model of the knowledge, skills, and abilities the user should attain and the instructional techniques, strategies, and processes needed to meet the goals of this model. This sort of modeling occurs in classroom learning where teachers continually assess what their students know, the level or degree to which they know it, and the most efficient ways to progress in achieving instructional goals. As discussed in the next section, this modeling is also found both implicitly and explicitly in effective technology-based instruction.

Similar modeling processes are also required to support performance aiding and decision-making, even though the emphasis in these applications is on problem solution

rather than on learning. What is needed is a model of the user to provide advice that can be understood and carried out, a model of the system or situation with which the user is interacting, and the ability to maintain something similar to an instructional dialogue to help the user identify correct solutions or decisions.

In both cases, concern with the knowledge, skills, and abilities that comprise human competence leads us to human cognition and the need to map current cognitive states onto goal cognitive states and determine what must be done next. This presents severe difficulties for classroom instruction (one teacher, many students). For instance, a problem arises from the degree to which students in a typical classroom vary in their prior knowledge, abilities, and learning progress. Research suggests variation by about a factor of five (e.g., Corno and Snow, 1986; Gettinger and White, 1980; Gustaffson and Undheim, 1996; Tobias, 1989). Especially important for military applications is the observation that variability in prior knowledge increases with age and may be more important in determining progress in post-secondary venues such as military training than it is for students in their earlier years of schooling. For both efficiency and effectiveness, such variability suggests the importance of tailoring interactions in military education, training, and performance aiding to the specific needs of individual users.

Assessment of cognition in classroom instruction is necessarily both informal and imprecise. If we seek to achieve human performance outcomes reliably (anytime, anywhere) and affordably, we must have recourse to technology. If we are to use computer technology to achieve these ends, we must be able to represent—or model in digital form—current cognitive states, goal states, and ongoing progress from one to the other. The empirical results discussed previously, arising from technology-based education, training, and performance aiding, suggest to some degree that we have been successful in doing this. The question then naturally arises as to how well our ability to implement and use such models meets the need for them.

C. THE CURRENT STATE OF COGNITIVE MODELING

1. Implicit Cognitive Models

Cognitive models are implemented implicitly and explicitly in technology-based instruction. Consider the following sample instructional item, which is typical of much—perhaps most—computer-mediated instruction:

In the multiplication problem $3 \times 4 = 12$, the number 12 is called a ________.

A. Factor {Branch to remedial X1}

B. Quotient {Branch to remedial X2}

C. Product {Reinforce, go to next}

D. Power {Branch to remedial X3}

In this item, the system (the computer instructor) assumes that a student responding "A" misunderstands the meaning of "Factor" and lacks an understanding of "Product," or both. The student will be branched to some instructional materials intended to correct one or the other of these cognitive states and then will be returned to this item or one similar to it. The same type of remedial approach is applied to responses of "B" and "D." A student responding with "C" may be rewarded (i.e., reinforced) with positive feedback and is then sent to whatever item will continue progress toward the instructional goal(s)—an action that, by itself, may constitute positive reinforcement.

The preceding example appears in an article by Norman Crowder written for automated teaching (Crowder, 1959). We can assume that the use of cognitive models is a not recent innovation in technology-based instruction, but a model of cognition and instructional progress is evident in this approach. It covers transitions from unlearned to learned states and illustrates what Crowder called "intrinsic" programming. This approach stands in contrast to the expensive and difficult-to-prepare "extrinsic" programming advocated by B. F. Skinner (e.g., 1954), and, for reasons of economy and utility, it is the dominant approach still in use today in technology-based instruction. It also covers many subject matters, posing questions following text paragraphs, graphic displays, simulations, audio presentations, video sequences, and/or other sources of instructional content, but the underlying logic remains the same as Crowder's original: display something, elicit a response, and branch to remedial or reinforcing material depending on the response.

To prepare an instructional item, a developer must anticipate and prepare responses for several discrete cognitive states, represented by the correct answer (response C) and the "distractors" (responses A, B, and D) to the item. The cognitive model represented by these states is static, implicit, and limited, but it is there. The main difference between the cognitive modeling in Crowder's and Skinner's approaches and the cognitive modeling being developed today is that the earlier models for intrinsic and extrinsic programming were implicit, embodied in the program of instruction, whereas today developers are

attempting to use more explicit models of cognition that can be abstracted, expressed, and validated separately from the systems in which these models are used.

2. Explicit Cognitive Models: Quantitative

These more explicit cognitive models are being used for applications such as intelligent tutoring systems (ITSs) and the human behavior modeling needed to generate computer (automated) military forces for constructive and virtual simulation. Explicit models of cognition were also applied early on (in the 1960s). These simple models were intended to account for rudimentary learning objectives that could be reduced to something like the substantial amounts of stimulus-response, associative pairing required to learn material such as arithmetic "facts" (addition, subtraction, multiplication tables), second language vocabulary, and technical jargon (names and functions of biological or mechanical structures). Nonetheless, they led to sophisticated and effective instructional approaches, and the line of research needed to determine the full range of learning situations and objectives to which they could be applied was begun but left unfinished and is rarely found today.

As an example of this approach (and its use of cognitive models), consider the following model of learning (adapted from Paulson, 1973), which attempted to account for the probability that a particular item for a particular learner would transition from the unlearned state (U), to either a short-term learned state (S) [i.e., present in working memory (WM)] or to a long-term learned state (L) [i.e., stored in long-term memory (LTM)]:

		State on Trial n+1			
		L	**S**	**U**	**P (correct)**
State on Trial n	**L**	1	0	0	1
	S	c	1–c	0	1
	U	a	b	1–a–b	g

In words:

- If a learned item (state L) is presented, then:
  - With probability = 1, it stays there.

- If an unlearned item (state U) is presented:
  - With probability = a, it will transition to LTM and the learned state.
  - With probability = b, it will transition to a short-term state (S) in WM, from which it can either be learned or forgotten.
  - With probability = 1–a–b, it will remain unlearned.
- If an item is in short-term WM (state S):
  - With probability = c, it will transition to LTM and the learned state.
  - With probability = 1–c, it will remain in the short-term state.
- An item in the short-term state will not slip back to the unlearned state.

This formulation accounts for guessing. As shown in the right-most column in the previous model of learning matrix, Paulson assumed a probability = g (presumably for "guessing") of a correct answer to an unlearned item but assumed a probability = 1 for a correct answer to an item in the learned or short-term state. The parameters are estimated for each item-student combination.

A key feature of this model is that it accounts for items that are not presented on a trial. In Paulson's formulation, which is based on Rumelhart's General Forgetting Theory (1967), when an item is not presented, transitions between states are expected to occur in accord with the following transition matrix:

		State on Trial n+1		
		L	S	U
State on Trial n	L	1	0	0
	S	0	1–f	f
	U	0	0	1

In words, when an item is not presented:

- If it is in the learned or unlearned state, it stays there.
- If it is in the short-term state, it may regress to the unlearned state with probability f or remain in the short-term state with probability 1–f.

Formulations such as this, which are based on explicit transition models of memory, led to an instructional strategy that has proven to be optimal in maximizing the number of items learned in the total time set aside for instruction, T, and allowing for a predetermined

number of items, N, to be presented in a single session (e.g., Atkinson and Paulson, 1972). The optimal solution determines which N items to present to a particular student so that the total number of items the student learns is maximized at time T. The solution is roughly the following:

- Before each trial, identify the item or items in N that have received the fewest number of correct responses since the last error.
- If only one item is identified, present that item. If more than one item is identified, select from this group the item or items that have been presented the fewest number of times.
- If only one item remains, present that item. If more than one item remains, select one at random and present it.

This description does not describe how items that have reached criterion in the current pool of N items can be optimally replaced with new items. Atkinson and Paulson (1972) and Chant and Atkinson (1973) have discussed such procedures.

Quantitative models of this sort continue to be used in technology-based instruction, as evidenced by efforts to apply Bayesian networking to assess the cognitive states of learners (e.g., Van Lehn and Niu, 2001). These models use Bayes' theorem to work backward from users' responses to determine the probabilities that they are using (perhaps have learned) specific cognitive processes. This approach can lead to quite sophisticated models of learners' knowledge and skills.

Three points may be worth making here:

1. Both implicit and explicit models of cognition and cognitive processes have been used in technology-based instruction from its beginning.
2. Fairly simple cognitive models for fairly simple instructional paradigms can lead to sophisticated and effective instructional strategies.
3. This approach remains a promising line of quantitative research that deserves to be explored more fully.

3. Explicit Cognitive Models: Qualitative

A line of R&D in cognitive modeling that has been more vigorously pursued in recent years is less quantitative than the preceding models, but the range of cognition covered tends to be more comprehensive and can be used to meet a wider range of learning objectives. This work typically comes under the heading of "human behavior modeling" and is increasingly used in the development of simulations for training personnel and units,

analyzing tactical, operational, and strategic alternatives, and designing, developing, and acquiring military materiel.

We are fortunate that several systematic and comprehensive analyses of these models have appeared recently, such as those by Pew and Mavor (1998), who reviewed 11 such models; Ritter et al. (2002), who reviewed 7 models not covered by Pew and Mavor; and Morrison (2003), who reviewed 19 such models.

In these reviews, the models selected for analysis were intentionally devised to be implemented in digital form (in computer algorithms). Doing this for any model is a significant demonstration. If a model can be represented in an algorithm, it can be tested. Using its algorithmic representation to capture and test cognitive processes can significantly enhance our knowledge of these processes and the effectiveness of our education, training, and performance-aiding applications. Diagnostic information that indicates where the model is correct will demonstrate the validity of the model, and diagnostic information that indicates where the model is incorrect will suggest where it must be modified to account for the full range of human cognition. Significant scientific and technological advances, as well as substantial improvements in our ability to educate, train, and assist military personnel, can arise from this sort of information.

As Morrison (2003) points out, most of these models are systems of if-then, condition-response ("production") rules that simulate cognitive structures and processes. Table 1 summarizes the 19 models he reviewed. These models provide a snapshot of the current state of human cognition and behavior representation.

How can these models contribute to the development of computer-mediated learning and performance-aiding environments? As suggested previously, a model intended to support education and training needs either an implicit or explicit model of cognition if it is to assess the state of a learner's knowledge, skill, and abilities. To do this, it must represent memory and its interactions with other cognitive functions, such as perception and attention. It can also represent cognitive functions such as decision-making and problem solving and cognitive responses to the environment, such as social behavior and situation awareness (SA) and/or the extent of cognitive workload.

However, if a model is developed to support education and training, having it simply represent the current state of cognitive processing is not enough. It must also represent and project its evolution and development. In short, it must include a model of human learning.

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (Source: Morrison, 2003)

Model Name	Summary Description	Reference(s)
Atomic Components of Thought (ACT)	Intended to provide a unified theory of mind and a design basis for instructional environments (e.g., intelligent tutors, computer-generated forces) and human interfaces. Distinguishes between declarative knowledge (represented with semantic networks) and procedural knowledge (represented using if-then rules).	Lebiere, 2002 Anderson et al., 2002
Adaptive Resonance Theory (ART)	Family of neural net models designed to explain sensory-cognitive processes (e.g., perception, recognition, attention, reinforcement, recall, and WM). Postulates bottom-up (e.g., perceptions) and top-down (e.g., expectations, attention control) functions in WM that interact to produce learning.	Grossberg, 1976a; 1976b Krafft, 2002 http://web.umr.edu/~tauritzd/art
Architecture for Procedure Execution (APEX)	Intended to reduce the time and effort needed to develop models of human performance in complex, dynamic environments (e.g., simulations, explorations of human performance theories, and assessments of equipment design on human performance). Includes goal-directed action selection for tasks and procedures and resource allocation for perceptual (mostly visual), cognitive, and psychomotor functions.	Freed et al., 2002 http://www.andrew.cmu.edu/~bj07/apex
Business Redesign Agent-Based Holistic Modeling System (Brahms)	Models social and man-machine interactions. Uses agents to model interactions among physically dispersed groups (e.g., teams), and if-then rules ("detectables" and "beliefs") to model decision-making (via "thoughtframes") and behavior within the groups. Emphasizes ethnographic analyses and socio-technical work practices, activities shaped by socio-technical environment, and constructivist, situated cognition to model cognition and behavior.	Sierhuis and Clancey, 1997 Clancey et al., 1998 Acquisti et al., 2001
Cognition and Affect Project (CogAff) (with associated SimAgent toolkit)	Conceptual space for describing cognitive architectures. Integrates emotional and cognitive processes. Incorporates three layers of cognition (reactive, deliberative, and reflective or meta-cognitive), three layers of information processing (perception, central processing, and action), and three types of emotions (primary based on reaction, secondary based on deliberation, and tertiary based on reflection)—all producing different perceptual, memory, and motor functions.	Sloman, 2001; 2003 http://www.cs.bham.ac.uk/~axs/cogaff.html

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (Source: Morrison, 2003) (Continued)

Model Name	Summary Description	Reference(s)
Cognition as a Network of Tasks (COGNET) [with associated Generator of Interface Agents (GINA) and iGEN™ toolkits)	Intended for cognitive task analysis and description of work domains in multitask environments requiring contemplative, decision-oriented, open-ended responses. Uses three subsystems to represent information processing (sensory/perceptual, mental modeling, action/motor), four forms of if-then rule-based task knowledge (goal-directed task hierarchies, perceptual demons to guide attention, blackboard for organizing declarative information, and possible actions linked to time and resource requirements), and meta-cognitive functions. Allows interfacing with other applications.	Zachary et al., 2001 http://www.chiinc.com/cognethome.shtml
Cognitive Complexity Theory (CCT) (with associated GOMS Language and Evaluation Analysis-3 (GLEAN3) toolkit)	Focuses on human interface design, human-computer interaction, and sequential task performance. Employs device models (transition networks), user models (sequentially executed if-then rules, the fundamental CCT units of cognition, retrieve from LTM), and mental operators to represent covert cognitive processes.	Kieras and Polson, 1985 Kieras, 1999
Cognitive Objects within a Graphical EnviroNmenT (COGENT)	Intended solely to provide tools (via a visual programming environment that evolves with the model being built) for cognitive modeling, assuming functional modularity (cognition as interaction among semi-autonomous subsystems) and using low-level processing components.	Cooper, Yule, and Sutton, 1998 Yule and Cooper, 2000 http://cogent.psyc.bbk.ac.uk
Concurrent Activation-Based Production System (CAPS)	Hybrid model for central cognitive functions (e.g., reading comprehension). Primary focus is on modeling brain activation patterns in high-level cognition via if-then rules for specific areas of the brain and associative networks for cognitive subsystems. Total activation in WM is capped, concerned exclusively with declarative knowledge (facts), but with different limits for different individuals. LTM includes procedural and declarative knowledge.	Just, Carpenter, and Varma, 1999 http://coglab.psy.cmu.edu/projects_set.html

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (Source: Morrison, 2003) (Continued)

Model Name	Summary Description	Reference(s)
Construction-Integration Theory (C-I Theory)	Uses a symbolic theory of sentence comprehension and propositions (actions and objects of the action) and stresses goal formation to provide a general model of cognition. Comprehension progresses from approximations to verified integration through mutually reinforced associations and spreading activation in memory. Extended to cover comprehension of novel computer interfaces [LInked model of Comprehension-based Action planning and Instruction (LICAI)] and new Web sites [Comprehension-based Linked model of Deliberate Search (CoLiDeS) model] and to incorporate concepts from Latent Semantic Analysis (LSA) used to derive meaning from text.	Kintsch, 1998 Landauer and Dumais, 1997 Kitajima and Polson, 1997 Kitajima, Blackmon, and Polson, 2000 http://psych-www.colorado.edu/ics
Distributed Cognition (DCOG)	Intended to model individuals' expert behavior with agents that use multiple strategies to respond to a complex environment (air traffic control). Based on a two-dimensional (2-D) space: abstraction with three levels (skill-based responses to signals, rule-based responses to signs, and knowledge-based responses to symbols) and decomposition (ranging from individual component to total system processing). Processing within this space depends on the level of expertise, the workload environment, and an individual's preferred level of engagement.	Eggleston, Young, and McCreight, 2000; 2001
Executive Process/ Interactive Control (EPIC)	Intended to model details of peripheral cognitive processes, input (perception), and output (psychomotor responses) to inform human-system interface design by predicting the order and timing of responses. Includes long-term storage of declarative and procedural knowledge and WM for assessing their application. Capacity and retrieval limitations arise only from perceptual and/or psychomotor systems, not from central memory store.	Kieras and Meyer, 1995 http://www.eecs.umich.edu/~kieras/epic.html
Human Operator Simulator (HOS)	Intended to inform human-system interface design by modeling human performance based on the sequence and timing of subtasks organized in networks. Uses simulation objects (configuration of displays and controls), task networks (if-then rules selecting verb-object pairs used to manipulate the objects), and micro-models (times to complete required subtasks involving perception, information processing, and psychomotor responses) to determine human response times.	Wherry, 1976 Harris, Iavecchia, and Dick, 1989 Glenn, Schwartz, and Ross, 1992

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (Source: Morrison, 2003) (Continued)

Model Name	Summary Description	Reference(s)
Man-machine Integrated Design and Analysis System (MIDAS)	Intended to inform human-system interface design by modeling individuals and interactions among individuals in performing multiple, concurrent tasks. Uses sensory input [operators and perceivable (detectable, recognizable, and identifiable) objects], memory [with declarative (beliefs in LTM, contexts in WM) and procedural components], decision-making, attention (with limitations on processing resources), SA (actual and perceived), and psychomotor output to model human operator limitations and capabilities.	Corker and Smith, 1993 Hart et al., 2001 http://caffeine.arc.nasa.gov/midas/index.html
Micro Systems Analysis of Integrated Network of Tasks (Micro SAINT) [may include the Integrated Performance Modeling Environment (IPME), using HOS micro-models, and WinCrew for estimating workload]	Simulation tool that uses a detailed task analysis to decompose human performance into a networked hierarchy (with branching logic and sequential dependencies) of discrete tasks and subtasks for which performance estimates can be validated. Network consists of subtask nodes (with launching conditions, time to complete, and effects) and relationships (that may be probabilistic, tactical requiring a threshold value, or multiple initiating more than one subtask). Designed to communicate with other models and applications through middleware.	Laughery and Corker, 1997
Operator Model Architecture (OMAR) (Flavors Expert (FLEX), an expert system toolkit, to model decision-making as a rule-following process)	Models human behavior as interactions among independent computational agents representing interacting individuals or cognitive processes within individuals. Allows both sequentially dependent and parallel task performance, with order determined by activation levels of tasks (without an explicit executive process). Allows facile interface with other models.	Deutsch, MacMillan, and Cramer, 1993 Deutsch, 1998 Cramer, 1998
PSI (Not an acronym)[1]	Attempts to integrate motivation with cognitive processes. Based on three levels of needs that interact to determine motive strength and specific goal behaviors: system needs (water and energy), preservation level (pain avoidance), and information level (certainty, competence, affiliation). Action strategies first seek automatized skills, then knowledge-based behavior, and then trial and error to satisfy goals.	Bartl and Dörner, 1998 Ritter et al., 2002 http://www.uni-bamberg.de/~ba2dp1/psi.html

[1] PSI is usually presented in all capital letters, but has not been defined as an acronym. According to Dietrich Dörner, "PSI is not an acronym. It just is the first letter of the Greek word for "soul". And this is because it is our intention with the PSI-project not only to simulate cognition, but motivation, emotion and what we call "action regulation" too. Just the whole soul! And that's the idea behind PSI" (personal communication, December 29, 2003).

Table 1. Summary Descriptions of Cognitive Aspects in Models Reviewed by Morrison (Source: Morrison, 2003) (Continued)

Model Name	Summary Description	Reference(s)
Situation Awareness Model for Pilot-in-the-Loop Evaluation (SAMPLE)	Generalized from original effort to model SA of pilots and air crews in air combat. Uses cognitive task analyses, pattern recognition from Klein's Recognition-Primed Decision-Making, Endsley's three levels of awareness (detection, identification, and prediction), and Rasmussen's three tiers of action strategy (skill-based pattern recognition, standardized if-then rules, and knowledge-based problem solving) to provide three stages of processing: information processing (with a continuous state estimator and a discrete event detector), situation assessment (with the information fusion and reasoning required by multitasking), and decision-making (with a procedure selector and a procedure executor). Output includes information disparity, SA disparity, and combat advantage index.	Rasmussen, 1983 Endsley, 1988 Klein, 1989 Mulgund, Harper, and Zacharias, 2000
State, Operator, And Result (Soar)	Intended as a comprehensive model of human cognition focused on operational task domains depicting all behavior as goal-driven movement through problem spaces that define states and operators for the task(s) at hand. Uses a four-cycle iterative process involving input (via human perception), elaboration (matches if-then, condition-action rules in LTM with those in WM to issue proposals for decision-making and direct commands for psychomotor actions), output (psychomotor execution), decision (either selects operators or identifies "impasses" requiring a new subgoal until all impasses are resolved). Uses a single process for LTM, learning, task representation, and decision-making. All learning occurs through "chunking," which occurs through impasse subgoaling and resolution. Emotions arise from SA clarity and confusion. Integrates individual and team knowledge and allows goals and plans to be shared among team members.	Lewis, 2001 http://ai.eecs.umich.edu/soar http://www-2.cs.cmu.edu/afs/cs/project/soar/public/www/home-page.html http://www.isi.edu/soar/soar-homepage.html http://www.nottingham.ac.uk/pub/soar/nottingham/soar-faq.html http://phoenix.herts.ac.uk/~rmy/cogarch.seminar/soar.html

Table 2, taken directly from Morrison (2003), summarizes the cognitive functions covered by the models summarized in Table 1. It indicates which models explicitly represent one or more of the following cognitive processes: perception, psychomotor performance, attention, SA, short-term memory (STM), LTM, learning, decision-making, problem solving, cognitive workload, emotional behavior, and social behavior.

Table 2. Cognitive and Behavioral Functions Represented in Models Reviewed by Morrison (Source: Morrison, 2003)

	Cognitive Function Required											
Acronym/ Abbreviation	Perception	Psychomotor Performance	Attention	Situation Awareness (SA)	Short-term Memory (STM)	Long-term Memory (LTM)	Learning	Decision-Making	Problem Solving	Cognitive Workload	Emotional Behavior	Social Behavior
ACT	X	X	X		X	X	X	X	X			
ART	X		X		X	X	X	X				
APEX	X	X				X		X				
Brahms	X	X				X		X				X
CogAff	X	X			X	X		X			X	
COGNET	X	X	X	X	X			X	X	X		
CCT	X	X			X	X		X				
COGENT					X	X	X	X				
CAPS			X		X	X		X	X			
C-I Theory			X		X	X		X				
DCOG	X		X		X	X		X		X		
EPIC	X	X			X	X		X				
HOS	X	X	X		X			X				
MIDAS	X	X	X	X	X	X		X				X
Micro SAINT	X		X			X		X		X		
OMAR	X		X			X		X				X
PSI	X	X	X		X	X	X	X	X		X	
SAMPLE	X		X	X		X		X				X
Soar	X	X	X	X	X	X	X	X	X		X	X

Table 2 indicates that

- All 19 models represent decision-making, but it is largely the reactive form of decision-making captured in if-then rules.
- All 19 models represent either STM or LTM.
- Perception and attention were well represented in 16 of the reviewed models.

- Although only four of the models explicitly represented SA, the functions of SA were present in those representing perception and attention.
- Social behavior was represented in only five of the models.
- Emotional behavior was represented in only three of the models.
- Learning and problem solving were represented in only five of the models. Morrison suggests that this limited representation may be caused by the nature of condition-response production models, which can react to the situations contained in anticipated if-states but which may not adapt well, if at all, to the unanticipated states and conditions that must be accommodated in learning and problem solving.

The five models judged to represent learning are ACT, COGENT, CAPS, PSI, and Soar. All five of these models also represent LTM, STM, and decision-making. All five of these models, except COGENT, also represent perception, psychomotor performance, and attention.

A model of cognition that includes learning is necessary for education and training applications, but it is not sufficient. A model of learning is not a model of instruction. All 19 models, as good as many of them are, lack a model of instruction. This component is needed to suggest links between specific instructional interventions and specific learning outcomes—teaching strategies that reliably bring about transitions from the learner's current cognitive state to one capable of producing the intended instructional outcomes.

D. INSTRUCTIONAL SYSTEMS DEVELOPMENT

Attaining a "model of instruction" that is centered around models of human cognition would lead to what might be called "engineering of instruction"—instruction viewed as neither art nor science, but as a way to produce specified instructional outcomes reliably and efficiently. Such a capability for development of instructional and performance-aiding systems should be based on empirically derived principles that can be applied realistically. Outcomes might consist of general objectives, such as the ability to transfer knowledge, long-term retention of knowledge and skill, motivation to continue learning, speed of response, accuracy of response, and so forth. The outcomes might be associated with more specific training objectives, such as the ability to locate single component failures in the XYZ power supply, pack a reserve parachute, or devise tactical plans.

Fragments of such a capability for engineering instruction have been identified in research literature, data, and findings. Work is needed to organize, substantially expand, and

include them as principles to be incorporated in current models of cognition. In addition, the engineering of instruction requires—as an essential foundational element—robust human cognitive models to enable the training, education or performance-aiding system to "know" the user and to adapt dynamically to the user's state.

1. What R&D Do We Need?

This brief review of cognitive models applied to automated instructional and performance-aiding systems suggests that good progress has been made but that much remains to be done. The models needed to support fully the broad range of human behavior required for simulations now used in training, analysis, and acquisition are not available. More generally, still lacking are the comprehensive models needed to represent subject matter expertise, levels of student learning, and, most especially, the links between specific instructional interventions and the development of specifically targeted cognitive abilities needed for competent performance.

The question, therefore, is: What R&D should be pursued to achieve short-, mid-, and long-term enhancements in the state of the art? This issue was addressed in a November 1999 workshop that assessed the R&D needed to support the Department of Defense (DoD) Advanced Distributed Learning (ADL) initiative (Final Report, 1999), in a series of workshops sponsored in 2002–2003 by the Learning Federation (Learning Federation, 2003), and in another human factors modeling (HFM) symposium (Foster and Fletcher, 2002). These three sources cover a wide range of issues and organize their results in different categories, but some common findings, specifically those concerned with research necessary for the development of cognitive models, emerge from them. Table 3 summarizes findings concerning cognitive modeling. It presents these findings as issues and indicates some specific research needed to meet these goals and fill gaps in our current capabilities.

The efforts suggested by Table 3 are realistic because they are amenable to research that can be performed with approaches available from our current state of knowledge. They suggest goals that can be achieved to an appreciable degree in the next 3 to 5 years. Doing so will be worth the effort and, for the success of our operational capabilities, the return on investment will outweigh the cost.

The value of cognitive models has another increasingly important dimension. The current world environment presents significant challenges to our capabilities for preparing military personnel to meet these challenges and thereby to our capabilities for providing

Table 3. Issues and Research Requirements for the Development of Cognitive Modeling Summarized From Assessments of Learning Technology Needs

Issue	Research Requirements
Cognitive theory	• Representation of "higher order" cognitive capabilities (e.g., decision-making, problem solving, meta-cognition, pattern recognition, critical thinking, situational awareness, teamwork) • New concepts and theories of cognition and cognitive workload based on new measurement capabilities • Valid and verified representation of expertise and its development in complex, ill-structured environments • Knowledge representations and ontologies that allow interoperability and logical operations within and across disciplines
Human behavior representation (HBR)	• Comprehensive and accurate representation of individual and of crew, team, and unit expertise, capabilities, and performance • Free, cognitively transparent exchange of virtual (avatar) and actual users in crew, group, and team learning
Cognitive model authoring	• Automated development, verification, and validation of cognitive models • Automated processes for performing cognitive analysis and cognitive readiness assessment • Automated capture of expertise: self-generating, self-modifying databases built from cases and examples of successful problem solving and decision-making • Principles for developing physically and cognitively realistic avatars
User assessment and representation	• New forms of computer-administered assessment items using the full display, timing, and natural language understanding capabilities of technology • Generation of valid, unobtrusive near-real-time assessment from interactions of individuals, teams, crews, and units with the learning or performance-aiding environment • Representation of subject matter misunderstandings and their sources • Generation and use of questions to build cognitive profiles of users • Assessment of cognitive workload • Assessment of the high-level cognitive skills needed to deal with unanticipated and unexpected situations
Management of progress	• Ability to match instructional or problem-solving goals with current state of the user and to generate or select optimal tutorial and/or problem-solving strategies • Automated principles of design and presentation needed to ensure reliable achievement of a targeted cognitive state(s) by individuals, crews, teams, and units • Automated principles for the development of higher-level cognitive skills such as creativity, adaptability, problem solving, and SA • Comprehensive understanding of meta-cognition and its development • Comprehensive understanding of incentive management and its interaction with cognitive development • Technology-based tools allowing distributed users to manage their own progress and problem solving • Predictions of learning rate and success from user profile information
User interface	• Management of user dialogue based on model of user cognitive abilities, style, and progress toward objective(s)

military education and training. We have responded in ways that have proven successful in the past, with task lists, essential task lists, mission-essential task lists, and even joint mission-essential task lists. These task lists suggest education and training objectives that we know how to meet.

2. Preparing for the Unexpected

The current asymmetric, unpredictable operational environment now facing our military personnel will inevitably present situations that are unexpected and for which they may not be fully prepared. Our military and our allies will have to respond to these situations with agility, flexibility, creativity, and skillful leadership. Their readiness to acquire the additional capabilities needed to meet these unexpected, unforeseen challenges will contribute substantially to the success of their operations. How, then, can we best prepare our people to expect the unexpected and deal with it successfully? One important aspect of this readiness is a cognitive capability. It places special demands on our ability to model cognition and to train individuals and units. It is an essential component of what we have called cognitive readiness (Etter, Foster, and Steele, 2000), and a combination of technology-based education, training, and performance aiding is expected to help our forces achieve it.

The components of cognitive readiness cover issues that include the following:

- **SA.** This is generally defined as the ability to perceive oneself in relation to the enemy and the environment. SA has been shown to improve with practice and instructional feedback.
- **Memory.** This is described as an active, reconstructive process supported by two underlying theoretical mechanisms: encoding specificity, which stresses the importance of external and internal cues, and transfer-appropriate processing, which stresses actions performed during encoding and retrieval. Tradeoffs exist between instruction used to enhance the retention and speed of initial acquisition. Conditions of learning, particularly those providing overlearning, can be designed to improve retention.
- **Transfer of training.** This is described as the ability to apply what is learned in one performance context to another performance context. Massive amounts of practice with feedback will improve "low-road" transfer and require little cognitive mediation. Training in forming mindful, conscious abstraction will improve "high-road" transfer, which requires cognitive mediation.
- **Metacognition.** This refers to the executive functions of thought, particularly those pertaining to knowledge and regulation of one's cognitive processes and

progress toward accepted goals. Metacognitive skills can be improved by exercises designed to increase the awareness of self-regulatory processes.

- **Automaticity.** This refers to processes that are performed rapidly, requiring few attentional resources. Practice with feedback and overlearning can produce automatic processing in many tasks.
- **Problem solving.** This transforms goals and subgoals into a plan of action by processes such as trial and error, proximity, fractionation, and knowledge-based referrals. Techniques for problem solving matched to goal and situation categories can be successfully taught, as can the information base needed for "strong" problem-solving methods, which depend on acquired knowledge.
- **Decision-making.** This is described as the selection of tactical and strategic plans, which are frequently primed by the recognition of learned patterns. Formal instruction in decision-making techniques may improve the quality of decisions, but some aspects of successful decision-making are determined by individual dispositions.
- **Mental flexibility and creativity.** This can be cast as problem solving. It applies "strong" methods, which are based on acquired knowledge and skills, and "weak" methods, which are used for poorly defined, ill-structured, chaotic tasks. Creativity may be more closely associated with the "weak" methods. The ability to train these weak methods directly is unclear from the research. It seems more likely that native abilities determine the facility with which people apply appropriate weak methods (i.e., achieve "creative solutions") to novel situations.
- **Leadership.** This appears to consist of motivational patterns and a combination of technical, conceptual, and interpersonal skills—the last being the most difficult to acquire and measure. However, the technical and conceptual skills needed by leaders can, to an appreciable extent, be taught. Interpersonal skills and patterns of motivation required for leadership appear to be more dependent on native abilities and are thus more difficult to teach.
- **Emotion.** This must be channeled and controlled if military personnel are to perform complex tasks under the stress and confusion that accompany modern military operations. Deeply engaging, sensory-immersing simulations provide promise for training warfighters to retain critical pieces of information and to perform under highly stressful conditions.

These issues have been discussed extensively in research literature, and Morrison and Fletcher (2002) have discussed their specific relevance to cognitive readiness. The points to be emphasized are that

- The assessment and development of the capabilities suggested by these issues will key on the adequacy of the cognitive models on which our education, training, and performance aiding are based.
- The adequacy of our cognitive modeling is a matter of first importance in the current unpredictable operational environment.

E. SUMMARY

The modeling efforts reviewed in this document, along with similar efforts involving human cognition, represent significant opportunities for cooperative research by the North Atlantic Treaty Organization (NATO) community concerned with the human competence that is an essential component of every military operation. We should respond to the opportunities they present.

REFERENCES

Acquisti, A., Clancey, W.J., van Hoof, R., Scott, M., and Sierhuis, M. (2001, December). *Brahms tutorial* (Technical Memorandum TM01-0002, Version 0.9.9.4 RFC). Moffett Field, CA: NASA Ames Research Center.

Anderson, J.R., Bothell, D., Byrne, M.D., and Lebiere, C. (2002, September). *An integrated theory of the mind*. [Manuscript submitted for publication].

Atkinson, R.C., and Paulson, J.A. (1972). An approach to the psychology of instruction. *Psychological Bulletin*, *78*, 49–61.

Bartl, C., and Dörner, D. (1998). *Comparing the behaviour of PSI with human behavior in the BioLab game* (Memorandum Number 32). Bamburg, Germany: Universität Bamburg: Lehrstuhl Psychologie II.

Bloom, B.S. (1984). The 2 sigma problem: The search for methods of group instruction as effective as one-to-one tutoring. *Educational Researcher*, *13*, 4–16.

Chant, V.G., and Atkinson, R.C. (1973). Optimal allocation of instructional effort to interrelated learning strands. *Journal of Mathematical Psychology*, *10*, 1–25.

Clancey, W.J., Sachs, P., Sierhuis, M., and van Hoof, R. (1998). Brahms: Simulating practice for work systems design. *International Journal of Human-Computer Studies*, *49*, 831–865.

Cooper, R., Yule, P., and Sutton, D. (1998). COGENT: An environment for the development of cognitive models. In U. Schmid, J.F. Krems, and F. Wysotzki (Eds.), *A cognitive science approach to reasoning, learning, and discovery* (pp. 55–82). Lengerich, Germany: Pabst Science Publishers.

Corker, K.M., and Smith, B.R. (1993). An architecture and model for cognitive engineering simulation analysis: Application to advanced aviation automation. In *Proceedings of the AIAA Computing in Aerospace 9 Conference*. Santa Monica, CA: American Institute of Aeronautics and Astronautics (AIAA).

Corno, L., and Snow, R.E. (1986). Adapting teaching to individual differences among learners. In M.C. Wittrock (Ed.), *Handbook of research on teaching* (3rd ed., pp. 605–629). New York: Macmillan.

Cramer, N. (1998). Distributed-OMAR: Reconfiguring a Lisp system as a hybrid Lisp/(Java) component. Paper presented at the *Lisp Users Group Meeting*. Berkeley, CA: Association of Lisp Users (ALU).

Crowder, N.A. (1959). Automatic teaching by means of intrinsic programming. In E. Galanter (Ed.), *Automatic teaching: The state of the art* (pp. 109–116). New York, NY: John Wiley and Sons.

Deutsch, S. (1998). Multi-disciplinary foundations for multiple-task human performance modeling in OMAR. Paper presented at the *Twentieth Annual Meeting of the Cognitive Science Society*. Madison, WI: Cognitive Science Society.

Deutsch, S.E., MacMillian, J., Cramer, N.L. (1993). *Operator Model Architecture (OMAR) demonstration final report* (AL/HR-TR-1996-0161). Wright-Patterson AFB, OH: Armstrong Laboratory, Logistics Research Division.

Eggleston, R.G., Young, M.J., and McCreight, K.L. (2000). Distributed cognition: A new type of human performance model. In M. Freed (Ed.), *Simulating human agents: Papers from the 2000 AAAI Fall Symposium* (Technical Report FS-00-03) (pp. 8–14). Menlo Park, CA: AAAI Press.

Eggleston, R.G., Young, M.J., and McCreight, K.L. (2001). Modeling human work through distributed cognition. In *Proceedings of the 10th Conference on Computer-Generated Forces and Behavioral Representation*. Orlando, FL: Simulation Interoperability Standards Organization.

Endsley, M.R. (1988). Design and evaluation for situation awareness enhancement. In *Proceedings of the 32nd Annual Meeting of the Human Factors Society* (pp. 97–101). Santa Monica, CA: Human Factors Society.

Etter, D.M., Foster, R.E., and Steele, T.P. (2000). Cognitive readiness and advanced distributed learning. *Crosstalk: The Journal of Defense Software Engineering*, *13*, 5–6.

Final Report: Department of Defense Continuous Learning System for 2012 (1999). Washington, DC: United States Department of Defense, Director of Defense Research and Engineering.

Fletcher, J.D. (1997). What have we learned about computer-based instruction in military training? In R.J. Seidel and P.R. Chatelier (Eds.), *Virtual reality, training's future*? (pp. 169–177). New York, NY: Plenum Publishing.

Fletcher, J.D. (2002). Evidence for learning from technology-assisted instruction. In H.F. O'Neil Jr. and R. Perez (Eds.) *Technology applications in education: A learning view* (pp. 79–99). Hillsdale, NJ: Lawrence Erlbaum Associates.

Fletcher, J.D. and Johnston, R. (2002). Effectiveness and cost benefits of computer-based aids for maintenance operations. *Computers in Human Behavior*, *18*, 717–728.

Foster, R.E., and Fletcher, J.D. (2002). *Computer-based aids for learning, job performance, and decision-making in military applications: Emergent technology and challenges* (IDA Document D-2786). Alexandria, VA: Institute for Defense Analyses.

Freed, M., Dahlman, E., Dalal, M., and Harris, R. (2002). *Apex reference manual for Apex version 2.2*. Moffett Field, CA: NASA ARC.

Gettinger, M., and White, M.A. (1980). Evaluating curriculum fit with class ability. *Journal of Educational Psychology*, *72*, 338–344.

Glenn, F., Schwartz, S., and Ross, L. (1992). *Development of a Human Operator Simulator Version V (HOS-V): Design and implementation* (Research Note 92-PERI-POX). Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences.

Grossberg, S. (1976a). Adaptive pattern classification and universal recoding, I: Parallel development and coding of neural feature detectors. *Biological Cybernetics*, *23*, 121–134.

Grossberg, S. (1976b). Adaptive pattern classification and universal recoding, II: Feedback, expectation, olfaction, and illusions. *Biological Cybernetics*, *23*, 187–202.

Gustaffson, J., and Undheim, J.O. (1996). Indivdidual differences in cognitive functions. In D.C. Berliner and R.C. Calfee (Eds.), *Handbook of educational psychology* (pp. 186–242). New York: Macmillan Reference.

Harris, R., Iavecchia, H.P., and Dick, A.O. (1989). The Human Operator Simulator (HOS-IV). In G.R. McMillan, D. Beevis, E. Salis, M.H. Strub, R. Sutton, and L. Van Breda (Eds.), Application of human performance models to system design (pp. 275–280). New York: Plenum Press.

Hart, S.G., Dahn, D., Atencio, A., and Dalal, K.M. (2001). *Evaluation and application of MIDAS v2.0* (SAE Technical Paper 2001-01-2648). Warrendale, PA: The Society of Automotive Engineers.

Joyce, D. (2001). Fusing simulation and performance support – the winning combination for improving equipment readiness? In *Proceedings of the 2001 Interservice/Industry Training, Simulation, and Education Conference*. Arlington, VA: National Training Systems Association (NTSA).

Just, M.A., Carpenter, P.A., and Varma, S. (1999). Computational modeling of high-level cognition and brain function. *Human Brain Mapping*, *8*, 128–136.

Kieras, D.E. (1999). *A Guide to GOMS Model Usability Evaluation Using GOMSL and GLEAN3* [On-line publication]. Retrieved August 27, 2002, from the University of Michigan's Electrical Engineering and Computer Science Department Web site: http://www.eecs.umich.edu/people/kieras/GOMS/GOMSL_Guide.pdf.

Kieras, D.E., and Meyer, D.E. (1995). *An overview of the EPIC architecture for cognition and performance with application to human-computer interaction* (EPIC Report No. 5). Ann Arbor, MI: The University of Michigan.

Kieras, D.E., and Polson, P.G. (1985). An approach to the formal analysis of user complexity. *International Journal of Man-Machine Studies*, *22,* 365–394.

Kintsch, W. (1998). *Comprehension: A paradigm for cognition*. New York: Cambridge University Press.

Kitajima, M., Blackmon, M.H., and Polson, P.G. (2000). A comprehension-based model of web navigation and its application to web usability analysis. In S. McDonald, Y. Waern, and G. Cockton (Eds.), *People and Computers XIV—Usability or Else* (Proceedings of HCI 2000) (pp. 357–373). Heidelberg, Germany: Springer-Verlag.

Kitajima, M., and Polson, P.G. (1997). A comprehension-based model of exploration. *Human-Computer Interaction*, *12*, 345–389.

Klein, G.A. (1989). Recognition-primed decisions. In W. Rouse (Ed.), *Advances in man-machine systems research, Volume 5* (pp. 47–92). Greenwich, CT: JAI Press.

Krafft, M.F. (2002, October). *Adaptive resonance theory*. Retrieved March 5, 2003, from the University of Zurich, Department of Information Technology Web site: http://www.ifi.unizh.ch/staff/krafft/papers/2001/wayfinding/html/node97.html.

Kulik, J.A. (1994). Meta-analytic studies of findings on computer-based instruction. In E.L. Baker and H.F. O'Neil, Jr. (Eds.), *Technology assessment in education and training*. Hillsdale, NJ: Lawrence Erlbaum Associates.

Landauer, T.K., and Dumais, S.T. (1997). A solution to Plato's problem: The latent semantic analysis theory of acquisition, induction, and representation of knowledge. *Psychological Review*, *104*, 211–240.

Laughery, K.R., Jr., and Corker, K. (1997). Computer modeling and simulation. In G. Salvendy (Ed.), *Handbook of human factors and ergonomics* (2nd ed.) (pp. 1375–1408). New York: John Wiley and Sons.

Learning Federation. (2003). *Learning science and technology: RandD, a roadmap to the future of learning*. Washington, DC: Federation of American Scientists.

Lebiere, C. (2002). *Introduction to ACT-R 5.0*. Tutorial presented at the 24th Annual Meeting of the Cognitive Science Society, CogSci 2002, August 2002. Fairfax, VA.

Lewis, R.L. (2001). Cognitive theory, SOAR. In N.J. Smelser and P.B. Baltes (Eds.), *International Encyclopedia of the Social and Behavioral Sciences*. Amsterdam: Pergamon (Elsevier Science).

Morrison, J.E. (2003). *A review of computer-based human behavior representations and their relation to military simulations* (IDA Paper P-3845). Alexandria, VA: Institute for Defense Analyses.

Morrison, J.E., and Fletcher, J.D. (2002). *Cognitive readiness* (IDA Paper P-3735). Alexandria, VA: Institute for Defense Analyses.

Mulgund, S.S., Harper, K.A., and Zacharias, G.L. (2000). SAMPLE: Situation Awareness Model for Pilot-in-the-Loop Evaluation. In *Proceedings of the 9th Conference on Computer Generated Forces and Behavioral Representation*. Orlando, FL: Simulation Interoperability Standards Organization (SISO).

Niemiec, R.P., Sikorski, M., and Walberg, H.J. (1989). Comparing the cost-effectiveness of tutoring and computer-based instruction. *Journal of Educational Computing Research*, *5*, 395–407.

Paulson, J.A. (1973). *An evaluation of instructional strategies in a simple learning situation* (Technical Report No. 209). Stanford, CA: Institute for Mathematical Studies in the Social Sciences, Stanford University.

Pew, R.W., and Mavor, A.S. (Eds.) (1998). *Modeling human and organizational behavior: Applications to military simulations*. Washington, DC: National Academy Press.

Rasmussen, J. (1983). Skills, rules, and knowledge: Signals, signs, and symbols and other distinctions in human performance models. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-13*, 257–266.

Ritter, F.E., Shadbolt, N.R., Elliman, D., Young, R., Gobet, F., and Baxter, G.D. (2002). *Techniques for modeling human and organizational behaviour in synthetic environments: A supplementary review*. Wright-Patterson AFB, OH: Human Systems Information Analysis Center.

Rumelhart, D.E. (1967). *The effects of inter-presentation intervals on performance in a continuous paired-associate task* (Technical Report No. 27). Stanford, CA: Institute for Mathematical Studies in the Social Sciences, Stanford University.

Sierhuis, M., and Clancey, W.J. (1997). Knowledge, practice, activities, and people. In B.R. Gaines and R. Uthurusamy (Eds.), *Artificial intelligence in knowledge management: Papers from the 1997 AAAI spring symposium* (Technical Report SS-97-01) (pp. 142–148). Menlo Park, CA: American Association for Artificial Intelligence.

Skinner, B.F. (1954). The science of learning and the art of teaching. *Harvard Education Review*, *24*, 86–97.

Sloman, A. (2001). Varieties of affect and the CogAff architectural scheme. From *Symposium on Emotion, Cognition, and Affective Computing*, Society for the Study of Artificial Intelligence and Simulation of Behaviour (AISB). Brighton, England: University of Sussex.

Sloman, A. (2003). How many separately evolved emotional beasties live within us? In R. Trappl, P. Petta, and S. Payr (Eds.), *Emotions in humans and artifacts*. Cambridge, MA: MIT Press.

Tobias, S. (1989). Another look at research on the adaptation of instruction to student characteristics. *Educational Psychologist*, *24*, 213–227.

VanLehn, K., and Niu, Z. (2001). Bayesian student modeling, user interfaces and feedback: A sensitivity analysis. *International Journal of Artificial Intelligence in Education, 12,* 154–184.

Wherry, R.J. (1976). The Human Operator Simulator – HOS. In T.B. Sheridan and G. Johannsen (Eds.), *Monitoring behavior and supervisory control* (pp. 283–293). New York, NY: Plenum Press.

Wisher, R.A., and Kincaid, J.P. (1989). *Personal electronic aid for maintenance: Final summary report* (ARI-RR-1516). Alexandria, VA: U.S. Army Research Institute. (DTIC/NTIS ADA 210 348)

Yule, P., and Cooper, R. (2000, August). The COGENT tutorial. Presented at the *22nd Annual Conference of the Cognitive Science Society*. Philadelphia, PA.

Zachary, W., Campbell, G.E., Laughery, K.R., Glenn, F., and Cannon-Bowers, J.A. (2001). The application of human modeling technology to the design, evaluation, and operation of complex systems. In E. Salas (Ed.), *Advances in human performance and cognitive engineering research, Volume 1* (pp. 199–247). New York: JAI Press.

GLOSSARY

2-D	two-dimensional
AAAI	American Association for Artificial Intelligence
ACT	Atomic Components of Thought
ADL	Advanced Distributed Learning
AFB	Air Force Base
AIAA	American Institute of Aeronautics and Astronautics
AISB	Artificial Intelligence and Simulation Behaviour
AL	Armstrong Laboratory
ALU	Association of Lisp Users
APEX	Architecture for Procedure Execution
ARC	Ames Research Center
ARI	U.S. Army Research Institute
ART	Adaptive Resonance Theory
Brahms	Business Redesign Agent-Based Holistic Modeling System
CAPS	Current Activation-Based Production System
CCT	Cognitive Complexity Theory
C-I Theory	Construction-Integration Theory
CogAff	Cognition and Effect Project
COGENT	Cognitive Objects within a Graphical Environment
COGNET	Cognition as a Network of Tasks
CoLiDeS	Comprehension-based Linked model of Deliberate Search
DCOG	Distributed Cognition
DDR&E	Director, Defense Research and Engineering
DoD	Department of Defense
DTIC	Defense Technical Information Center
EPIC	Executive Process/Interactive Control
FLEX	Flavors Expert

GINA	Generator of Interface Agents
GLEAN3	GOMS Language and Evaluation Analysis-3
GOMS	Goals, Operators, Methods, and Selection Rules
GOMSL	GOMS Language
HBR	human behavior representation
HFM	human factors modeling
HOS	Human Operator Simulator
IDA	Institute for Defense Analyses
IEEE	Institute of Electrical and Electronics Engineers
IPME	Integrated Performance Modeling Environment
ITS	intelligent tutoring system
LICAI	LInked model of Comprehension-based Action planning and Instruction
LSA	Latent Semantic Analysis
LTM	long-term memory
Micro Saint	Micro Systems Analysis of Integrated Network of Tasks
MIDAS	Man-machine Integrated Design and Analysis System
NASA	National Aeronautics and Space Administration
NATO	North Atlantic Treaty Organization
NTIS	National Technical Information Service
NTSA	National Training Systems Association
OMAR	Operator Model Architecture
R&D	research and development
SA	situation awareness
SAE	Society of Automative Engineers
SAMPLE	Situation Awareness Model for Pilot-in-the Loop Evaluation
SISO	Simulation Interoperability Standards Organization
Soar	State, Operator, And Result
STM	short-term memory
TM	Technical Memorandum
WM	working memory

REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED *(From–To)*
November 2003	Final	June 2003–August 2003

4. TITLE AND SUBTITLE

Modeling the User for Education, Training, and Performance Aiding

5a. CONTRACT NUMBER
DAS W01 98 C 0067/DASW01 04 C 0003

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)

Robert E. Foster, J.D. Fletcher

5d. PROJECT NUMBER

5e. TASK NUMBER
AK-2-2349

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Institute for Defense Analyses
4850 Mark Center Drive
Alexandria, VA 22311-1882

8. PERFORMING ORGANIZATION REPORT NUMBER

IDA Document D-2920

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)

ODUSD(S&T) (Human Systems)
1777 North Kent Street
Suite 9030
Rosslyn, VA 22209

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release; distribution unlimited. (29 November 2004)

13. SUPPLEMENTARY NOTES

14. ABSTRACT

Instruction that incorporates the substantial efficiencies of one teacher (a computer) for every student must employ models that represent the current and the objective states of the learner. These models must include learners' cognitive processes, which underlie the human skills, performance, and abilities needed for success in all military operations. These cognitive models are as necessary for performance aiding as they are for instruction. They must be self-generating and established in real time and on demand. Both implicit and explicit models have been used to accomplish these ends, and both types are briefly reviewed. Implicit models bind content and presentation strategy together, while explicit models keep the two separate. Early explicit models were largely quantitative, involving relatively simple learning paradigms. Current explicit models are more qualitative and deal with more complex and comprehensive paradigms. These models may be more suitable for today's uncertain, asymmetric operational environments, which frequently require responses that instructional developers can neither foresee nor prepare for in advance. These operational environments must prepare military personnel to expect the unexpected and meet it with individual and collective agility, creativity, and adaptability. These qualities require the use of powerful and comprehensive cognitive models to support programs of education, training, and performance aiding. Nineteen of these models are briefly reviewed and summarized.

15. SUBJECT TERMS

Advanced Distributed Learning (ADL), cognition, cognitive models, human factors modeling (HFM), military training, technology-based instruction

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					Dr. Robert Foster
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*
Uncl.	Uncl.	Uncl.	SAR	38	703-588-7437

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39.18